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The HSN MURI program has been organized in the past six years to address several challenging fundamental issues in sensor fusion and integration, automatic target recognition and tracking, and 3-D reconstruction of urban models based on heterogeneous sensor networks.

We are pleased to report that the team has had great success in our research endeavors, as evidenced numerically by

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ABSTRACT

The HSN MURI program has been organized in the past six years to address several challenging fundamental issues in sensor fusion and integration, automatic target recognition and tracking, and 3-D reconstruction of urban models based on heterogeneous sensor networks.

We are pleased to report that the team has had great success in our research endeavors, as evidenced numerically by the number of peer reviewed papers as well as a significant number of honors and best paper awards received by our team members. In this final scientific report, we summarize the key contributions in this program.

Enter List of papers submitted or published that acknowledge ARO support from the start of the project to the date of this printing. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

Received		Paper
2012/04/01 2:	165	Bela Bollobas, Svante Janson, Oliver Riordan. Sparse random graphs with clustering, Random Structures Algorithms, (05 2011): 0. doi:
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2008/09/22 1: 1 Yi Ma, Allen Yang, Harm Derksen, and Robert Fossum. Estimation of subspace arrangements with applications in modeling and segmenting mixed data., , ( ): . doi:

TOTAL: 113

Number of Papers published in peer-reviewed journals:

(b) Papers published in non-peer-reviewed journals (N/A for none)

Received Paper

2011/08/17 1! 137 Hossein Mobahi, Shankar R. Rao, Allen Y. Yang, S. Shankar Sastry, Yi Ma. Segmentation of Natural Images by Texture and Boundary Compression, International Journal of Computer Vision, (04 2011): 0. doi: 10.1007/s11263-011-0444-0

2010/03/16 1: 32 K. Varshney, A. Willsky. Classification using Geometric Level Sets, Journal of Machine Learning Research, (01 2010): . doi:

TOTAL: 2

Number of Papers published in non peer-reviewed journals:

(c) Presentations

1. E. Fox, D. Choi, and A. Willsky, “Nonparametric Bayesian Methods for Large Scale Multi-Target Tracking,” Asilomar Conference, 2006.

2. O. Kreidl and A.Willsky, “Decentralized Detection in Undirected Network Topologies,” IEEE Statistical Signal Processing Workshop, Madison, WI, Aug. 2007.

3. S. Sanghavi, V. Tan, and A.Willsky, “Learning Graphical Models for Hypothesis Tests,” IEEE Statistical Signal Processing Workshop, Madison, WI, Aug. 2007.

4. S. Oh, “Bayesian Formulation of Data Association and Markov Chain Monte Carlo Data Association,” in Science and Systems Conference (RSS) Workshop Inside Data association, ETH Zurich, Switzerland, June 2008.

5. J. Williams, J. Fisher, and A. Willsky, “A Constraint Generation Integer Programming Approach to Information-Theoretic Sensor Resource Management,” IEEE Statistical Signal ProcessingWorkshop, Madison, WI, Aug. 2007.

6. A. Zakhor, “Fast, Automated, 3D, Airborne Modeling of Large Scale Urban Environments,” 3DPVT, 2008.

7. E. Seto, A. Giani, V. Shia, C. Wang, P. Yan, A. Yang, M. Jerrett, and R. Bajcsy. “A wireless body sensor network for the prevention and management of asthma,” IEEE Symposium on Industrial Embedded Systems, 2009.

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10. Dheeraj Singaraju, Roberto Tron, Ehsan Elhamifar, Allen Yang, and Shankar Sastry. On the Lagrangian biduality of sparsity minimization problems. Signal Processing with Adaptive Sparse Structured Representations Workshop (SPARS), 2011.

Number of Presentations: 10.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received Paper

TOTAL:

Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received		Paper
2012/04/01 2:	159	Peter Volgyesi, Sandor Szilvasi, Janos Sallai, Akos Ledeczi. External Smart Microphone for Mobile Phones, International Conference on Sensing Technology. 2011/12/01 03:00:00, . : ,
2012/04/01 2	157	Janos Sallai, Akos Ledeczi, Peter Volgyesi. Acoustic Shooter Localization with a Minimal Number of Single-Channel Wireless Sensor Nodes, SenSys. 2011/11/01 03:00:00, . : ,
2012/04/01 1	155	Henrik Ohlsson, Allen Yang, Roy Dong, Shankar Sastry. Compressive Phase Retrieval From Squared Output Measurements Via Semidefinite Programming, System Identification Workshop. 2012/07/11 03:00:00, . : ,
2012/04/01 1	154	Victor Shia, Allen Yang, Shankar Sastry, Andrew Wagner, Yi Ma. Fast l1-Minimization and Parallelization for Face Recognition, Asilomar Conference on Signals, Systems, and Computers. 2011/10/31 03:00:00, . : ,
2012/04/01 1	153	Chris Slaughter, Allen Yang, Justin Bagwell, Costa Checkles, Luis Sentis, Sriram Vishwanath. Sparse Online Low-Rank Projection and Outlier Rejection (SOLO) for 3-D Rigid-Body Motion Registration, Internation Conference on Robotics and Automation. 2012/05/14 03:00:00, . : ,
2012/04/01 1	151	Hossein Mobahi, Zihan Zhou, Allen Yang, Yi Ma. Holistic 3D Reconstruction of Urban Structures form Low-Rank Textures, ICCV Workshop on 3D Representation and Recontruction. 2011/11/07 03:00:00, . : ,
2012/04/01 1	58	V. Tan, A. Anandkumar, A. Willsky. How do the structure and the parameters of Gaussian tree models affect structure learning?, Allerton Conference on Communication, Control and Computing. 2009/10/01 03:00:00, . : ,
2011/08/19 1:	143	Galen Reeves, Naveen Goela, Nebojsa Milosavljevic, Michael Gastpar. A compressed sensing wire-tap channel, IEEE Information Theory Workshop. 2011/10/16 03:00:00, . : ,
2011/08/17 1!	139	Galen Reeves, Michael Gastpar. On the role of diversity in sparsity estimation, IEEE International Symposium on Information Theory. 2010/06/13 03:00:00, . : ,
2011/08/17 1!	138	Nikhil Naikal, Allen Y. Yang, S. Shankar Sastry. Informative Feature Selection for Object Recognition via Sparse PCA, International Conference on Computer Vision. 2011/11/07 03:00:00, . : ,

TOTAL: 10

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

(d) Manuscripts

Received		Paper
2010/08/03 2	113	Galen Reeves and Michael Gastpar. "Compressed" Compressed Sensing, (01 2010)
2010/07/19 1	112	Zaihong Shuai, Songhwai Oh, Ming-Hsuan Yang. Traffic modeling and prediction using camera sensor networks, (09 2010)
2009/08/13 1	33	B. Bollobas, O. Riordan. Metrics for Sparse Graphs, ( )
2008/12/23 1	56	M. Kushwaha, S. Ohy, I. Amundson, X. Koutsoukos, A. Ledeczi. Target Tracking in Urban Environments using Audio-Video Signal Processing in Heterogeneous Wireless Sensor Networks, ( )
2008/10/01 1	95	Min Ding, Kristian Lyngbaek, Avideh Zakhor. Automatic registration of aerial imagery with untextured 3D LiDAR models, ( )
2008/10/01 1	94	Isaac Amundson, Branislav Kusy, Peter Volgyesi, Xenofon Koutsoukos, Akos Ledeczi. Time Synchronization in Heterogeneous Sensor Networks, ( )
2008/10/01 1	87	Jozsef Balogh, Bela Bollobas, Robert Morris. HEREDITARY PROPERTIES OF COMBINATORIAL STRUCTURES: POSETS AND ORIENTED GRAPHS, ( )
2008/10/01 1	86	Bela Bollobas, Oliver Riordan. Percolation on random Johnson–Mehl tessellations and related models, ( )
2008/10/01 1	85	Venkat Chandrasekaran, Jason Johnson, O. Patrick Kreidl, Dmitry Malioutov, Sujay Sanghavi, Alan S. Willsky. Message Passing and Distributed Statistical Inference, ( )
2008/10/01 1	84	Allen Y. Yang, Sameer Iyengar, Philip Kuryloski, Roozbeh Jafari, Shankar Sastry, Ruzena Bajcsy. Distributed Segmentation and Classification of Human Actions Using a Wearable Motion Sensor Network, ( )
2008/10/01 1	83	Phoebus Chen, Parvez Ahammad, Colby Boyer, Shih-I Huang, Leon Lin, Edgar Lobaton, Marci Meingast, Songhwai Oh, Simon Wang, Posu Yan, Allen Y. Yang, Chuohao Yeo, Lung-Chung Chang, Doug Tygar, S. Shankar Sastry. CITRIC: A LOW-BANDWIDTH WIRELESS CAMERA NETWORK PLATFORM, ( )
2008/10/01 1	81	Isaac Amundson, Manish Kushwaha, Branislav Kusy, Peter Volgyesi, Gyula Simon, Xenofon Koutsoukos, Akos Ledeczi. Time Synchronization for Multi-Modal Target Tracking in Heterogeneous Sensor Networks, ( )
2008/10/01 1	80	Emily B. Fox, Erik B. Sudderth, Alan S. Willsky. Hierarchical Dirichlet Processes for Tracking Maneuvering Targets, ( )
2008/10/01 1	50	Shankar R. Rao, Allen Y. Yang, S. Shankar Sastry, Yi Ma. Robust Algebraic Segmentation of Mixed Rigid-Body and Planar Motions, ( )
2008/09/26 1	57	I. Amundson, M. Kushwaha, B. Kusy, P. Volgyesi, G. Simon, X. Koutsoukos, A. Ledeczi. Time Synchronization for Multi-Modal Target Tracking in Heterogeneous Sensor Networks, ( )
2008/09/22 1	16	J. Balogh, B. Bollobas, R. Morris. Hereditary properties of combinatorial structures: Posets and oriented graphs, ( )
2008/09/22 1	11	B. Bollobas, O. Riordan. Percolation on dual lattices with k-fold symmetry, ( )
2008/09/22 1	8	B. Bollobas, O. Riordan. Percolation on random Johnson-Mehl tessellations and related models, ( )
2011/08/19 1	142	Galen Reeves, Michael Gastpar. Fundamental tradeoffs for sparsity pattern recovery, IEEE Transactions on Information Theory (06 2011)

TOTAL: 19

Number of Manuscripts:

Books

Received Paper

TOTAL:

Patents Submitted

1. A. Zakhor and M. Ding. Automated texture mapping system for 3D models. US Patent Application 20090110267, 2009.

2. Y. Ma, J. Wright, A. Yang, and S. Sastry. Recognition via High-Dimensional Data Classification. US Patent Application 61/025,039, 2009.

3. R. Bajcsy, A. Yang, R. Jafari, and S. Sastry. Improved System for Recognition of Human Actions. US Patent Application 61/119,861, 2009.

4. A. Ledeczi, P. Volgyesi, J. Sallai. System and Methods of Localization and Tracking of Wireless Nodes Using Varying Radio Frequency Signals. US Patent Application 61/107,912.

Patents Awarded

Awards

1. Shankar Sastry (PI) was appointed Dean of the College of Engineering at UC Berkeley, 2007.

2. Galen Reeves received a student travel award for the 2007 Statistical Signal Processing Workshop, 2007.

3. J. Kim, M. Cetin, and A. Willsky were awarded the 2008 Best Paper of the Year Award by the journal Signal Processing for their paper, ”Nonparametric Shape Priors for Active Contour-Based Image Segmentation,” Signal Processing, Vol. 87, No. 12, Dec. 2007, pp. 3021-3044.

4. Branislav Kusy, Akos Ledeczi, Xenofon Koutsoukos received Best Paper Award in 5th ACM Conference on Embedded Networked Systems (SenSys 2007), November 2007.

5. Xenofon Koutsoukos was elected a Senior Member, Institute of Electrical and Electronics Engineers (IEEE), September 2007.

6. Xenofon Koutsoukos was an Invited Panelist, Sensor Networks: Future Challenges and Applications, 17th International Conference on Computer and Communication Networks, St. Thomas, US Virgin Islands, August 3-8, 2008.

7. Subhransu Maji received a Google fellowship in Computer Vision Object Recognition, 2009.

8. Kush Varshney received a student travel award at the International Conference on Information Fusion, 2009.

9. Allen Yang, Subhransu Maji, Kirak Hong, Posu Yan, and Shankar Sastry received a Best Paper Award at the International Conference on Information Fusion, 2009.

10. Avideh Zakhor and Minghua Chen received the 2009 best paper award for IEEE Transactions on Multimedia for a 2006 paper.

11. A. Gu and A. Zakhor received a Best Paper Award from IEEE Transactions on Semiconductor Manufacturing, 2010.

12. N. Naikal, A. Yang, and S. Sastry received a Best Student Paper Award, Honorable Mention, at the International Conference on Information Fusion, 2010.

13. A. Yang and S. Sastry received a Best Student Paper Award at the Asian Conference on Computer Vision, 2009.

14. A. Willsky was elected to the National Academy of Engineering, 2010.

15. A.Willsky received the 2010 Technical Achievement Award from the IEEE Signal Processing Society.

16. Emily Fox received the Savage Award for the outstanding Ph.D. thesis in Applied Methodology in Bayesian Statistics.

17. Emily Fox received the Jin-Au Kong Outstanding Doctoral Thesis Prize from MIT’s Dept. of EECS.

18. Dmitry Malioutov, Mujdat Cetin, and Alan Willsky received the 2011 Best Paper Award from the IEEE Signal Processing Society.

19. Vincent Tan received the Jin-Au Kong Outstanding Doctoral Thesis Prize from MITs Dept. of EECS, 2011.

20. Bela Bollobas was elected to the Fellowship of the Royal Society, 2011.

Graduate Students

NAME	PERCENT_SUPPORTED	Discipline
Neal Bushaw	0.10	
Ago Riet	0.25	
Vivek Shandilya	0.20	
Dominik Vu	0.05	
Andrew Uzzell	0.10	
Min Ding	0.20	
Emily Fox	0.06	
Venkat Chandrasekaran	0.03	
Myung Jin Choi	0.01	
Matthew Johnson	0.01	
Oliver Kosut	0.08	
Ying Liu	0.01	
Kush Varshney	0.06	
John Lee	0.14	
Ariadna Quattoni	0.02	
Ekaterina Saenko	0.01	
Sy Bor Wang	0.06	
Christopher Wilkens	0.04	
Pei-Hsiu Yeh	0.05	
Parvez Ahammad	0.17	
Carl Blubaugh	0.05	
Matthew Carlberg	0.08	
Nicholas Corso	0.21	
Chunhui Gu	0.14	
Edgar Lobaton	0.20	
Subhransu Maji	0.39	
Nikhil Naikal	0.32	
Galen Reeves	0.64	
Jason Chang	0.04	
Michael Siracusa	0.10	
Dahua Lin	0.20	
Zoran Dzunic	0.21	
Isaac Amundson	0.48	
Manish Kushwaha	0.59	
Stephen Collins	0.17	
Sandor Szilvasi	0.20	
FTE Equivalent:	**5.67**	
Total Number:	**36**	

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
Animashree Anandkumar	0.90
Karen Livescu	0.03
Louis-Philippe Morency	0.14
Alex Berg	0.14
Dheeraj Singaraju	0.08
FTE Equivalent:	**1.29**
Total Number:	**5**

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
Shankar Sastry	0.01	Yes
Bela Bollobas	0.10	
Alan Willsky	0.04	Yes
Trevor Darrell	0.02	
Michael Gastpar	0.03	
Kannan Ramchandran	0.02	
Avideh Zakhor	0.09	
John Fisher	0.17	
Xenofon Koutsoukos	0.08	
Akos Ledeczi	0.10	
FTE Equivalent:	**0.66**	
Total Number:	**10**	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 0.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:...... 0.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):...... 0.00

Number of graduating undergraduates funded by a DoD funded Center of Excellence grant for Education, Research and Engineering:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and intend to work for the Department of Defense 0.00

The number of undergraduates funded by your agreement who graduated during this period and will receive scholarships or fellowships for further studies in science, mathematics, engineering or technology fields:...... 0.00

Names of Personnel receiving masters degrees

NAME	
Venkat Chandrasekaran	
Galen Reeves	
Z. Michael Chen	
Ying Liu	
James Saunderson	
Ariadna Quattoni	
Chunhui Gu	
Jason Chang	
John J. Lee	
Total Number:	**9**

Names of personnel receiving PHDs

NAME
Songhwai Oh
Parvez Ahammad
Dmitry Malioutov
O. Patrick Kreidl
Galen Reeves
Phoebus Chen
Edgar Lobaton
Jason Johnson
Isaac Amundson
Manish Kushwaha
Kush Varshney
Myung Jin Choi
Vincent Tan
Ashraf Tantawy
Emily Fox
Michael Siracusa
Subhransu Maji
Total Number: 17

Names of other research staff

NAME	PERCENT_SUPPORTED
Rachel Cohen	0.03
Justin Dauwels	0.18
David Wingate	0.06
Andreas Geiger	0.01
Kristen Grauman	0.03
David Demirdjian	0.01
Mudat Cetin	0.05
Kirak Hong	0.09
Steven Jian	0.03
John Kua	0.03
Kristian Lingbaek	0.03
Travis Pynn	0.21
Posu Yan	0.28
Allen Yang	0.89
Janos Sallai	0.17
FTE Equivalent:	**2.10**
Total Number:	**15**

Sub Contractors (DD882)

1 a. Massachusetts Institute of Technology

1 b. 77 Massachusetts Avenue

Cambridge MA 021394307

Sub Contractor Numbers (c): SA5211

Patent Clause Number (d-1): 252.227-7014

Patent Date (d-2): 6/1/1995 12:00:00AM

Work Description (e): Heterogeneous Sensor Webs for Automated Target Recognition and Tracking in Urban Terrain

Sub Contract Award Date (f-1): 5/1/2006 12:00:00AM

Sub Contract Est Completion Date(f-2): 1/31/2012 12:00:00AM

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1 a. Massachusetts Institute of Technology

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Sub Contractor Numbers (c): SA5211

Patent Clause Number (d-1): 252.227-7014

Patent Date (d-2): 6/1/1995 12:00:00AM

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Sub Contract Award Date (f-1): 5/1/2006 12:00:00AM

Sub Contract Est Completion Date(f-2): 1/31/2012 12:00:00AM

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1 a. The University of Memphis

1 b. Research Support Services

Administration Building 315

Memphis TN 38152

Sub Contractor Numbers (c): SA5213

Patent Clause Number (d-1): 252.227-7014

Patent Date (d-2): 6/1/1995 12:00:00AM

Work Description (e): Heterogeneous Sensor Webs for Automated Target Recognition and Tracking in Urban Terrain

Sub Contract Award Date (f-1): 5/1/2006 12:00:00AM

Sub Contract Est Completion Date(f-2): 1/31/2012 12:00:00AM

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1 a. Vanderbilt University

1 b. PMB # 407749

2301 Vanderbilt Place

Nashville TN 372407749

Sub Contractor Numbers (c): SA5212

Patent Clause Number (d-1): 252.227-7014

Patent Date (d-2): 6/1/1995 12:00:00AM

Work Description (e): Heterogeneous Sensor Webs for Automated Target Recognition and Tracking in Urban Terrain

Sub Contract Award Date (f-1): 5/1/2006 12:00:00AM

Sub Contract Est Completion Date(f-2): 1/31/2012 12:00:00AM

---

1 a. Vanderbilt University

1 b. Division of Sponsored Research
512 Kirkland Hall
Nashville TN 37240

Sub Contractor Numbers (c): SA5212

Patent Clause Number (d-1): 252.227-7014

Patent Date (d-2): 6/1/1995 12:00:00AM

Work Description (e): Heterogeneous Sensor Webs for Automated Target Recognition and Tracking in Urban Terrain

Sub Contract Award Date (f-1): 5/1/2006 12:00:00AM

Sub Contract Est Completion Date(f-2): 1/31/2012 12:00:00AM

Inventions (DD882)

Scientific Progress

Technology Transfer

Final Report

Heterogeneous Sensor Webs for Automated Target Recognition and Tracking in Urban Terrain

ARO MURI W911NF-06-1-0076

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TEAM MEMBERS:

UC Berkeley: S. Sastry (PI), T. Darrell, M. Gastpar, A. Zakhor
MIT: A. Willsky (co-PI), J. Fisher
Vanderbilt: X. Koutsoukos (co-PI), A. Ledeczi
Memphis: B. Bollobas (co-PI)

Abstract

The HSN MURI program has been organized in the past six years to address several challenging fundamental issues in sensor fusion and integration, automatic target recognition and tracking, and 3-D reconstruction of urban models based on heterogeneous sensor networks. In particular, our approach as outlined in the program proposal has been to achieve the following goals:

1. New theories of distributed signal processing with random spatio-temporal sampling of complex scenes for recognition and tracking of objects in heterogeneous sensor networks (HSNs).

2. Robust design principles for sensor networks with both low and high bandwidth sensors to automatically recognize and track targets in complex urban environments.

3. Metrics for the design and deployment of sensor webs, and theoretical bounds on the performance of different kinds of sensor webs.

4. Incorporate mobility into sensor webs, and develop algorithms that take into account mobility of nodes and the need to query sensor nodes using mobile assets.

We are pleased to report that the team has had great success in our research endeavors, as evidenced numerically by the number of peer reviewed papers as well as a significant number of honors and best paper awards received by our team members. Some of the most significant works are listed as follows:

1. Kusy, Ledeczi, and Koutsoukos received a Best Papaer Award at SenSys 2007.

2. Yang and Sastry received a Best Student Paper Award at ACCV 2009.

3. Alan Willsky was elected to the National Academy of Engineering in 2010 for contributions to model-based signal processing and statistical inference.

4. Gu and Zakhor received a best paper award from the IEEE Transactions of Semiconductor and Manufacturing in 2010.

5. Yang and Sastry's work on sparsity-based classification was a Top 100 Paper Download from IEEE in 2010.

6. Bela Bollobas was elected to the Fellowship of the Royal Society in 2011 for contributions in combinatorics.

7. Malioutov, Cetin, and Willsky received a Best Paper Award from the IEEE Signal Processing Soceity in 2011.

In this final scientific report, we summarize the key contributions in each of the above four Thrusts.

1 Thrust I: Sensor Fusion Algorithms for Heterogeneous Sensors

Investigators: John Fisher, Xenofon Koutsoukos, Akos Ledeczi, and Alan Willsky.

In Thrust I, we have been focused on the development of new frameworks on distributed signal processing and wireless data communications for heterogeneous sensor networks with computing, communication, and energy constraints.

1. Scalable Sensor Fusion for Graphical Models (Willsky & Fisher).

   This work began before the start of this MURI (and under its predecessor SensorWeb MURI) and has continued throughout the full length of this project. In the first year of the project our work in this area had several components. One of these was the development of a distributed detection network for near-optimal detection and localization of chemical releases [54] including extensive tradeoff analysis to determine an effective strategy for parsimonious communication with minimal loss in detection/localization performance. Our early work [37] also includes a summary of several aspects of our foundational work in adapting and extending graphical model inference methods to problems of distributed fusion, including work on distributed target tracking and data association via message-passing, error analysis in message-passing algorithms and implications for efficient encoding of messages, and sensor management in distributed tracking. Another early part of this component of our research, covered in [39–42], deals with the analysis of particular classes of distributed message-passing algorithms for Gaussian problems. This analysis, which involves so-called walk-sum computations that capture the informational flow as messages traverse walks from node to node in a network, provides easily checked and very broad sufficient conditions for convergence and optimality of large classes of algorithms as well as two other very important features for sensor networks, namely (a) provably optimal fusion performance for slightly modified algorithms that can accommodate transmission failures; and (b) adaptive methods for choosing, at each stage in the fusion process, the best set of messages (and hence walks) to send in order to maximize impact on fusion accuracy with minimal usage of communication resources. A third early component of this part of our research [86, 87] provides theoretical results making clear conditions that ensure optimality of max-product algorithms for so-called weighted matching problems. This is particularly relevant to problems in wireless networks and distributed fusion, as the "weights" can be set to capture either raw communication capacity or informational value, resulting in algorithms that yield, in an adaptive manner, the best set of paths to be used for communication or fusion in terms of maximizing weight subject to constraints on the load on each node.

   Another early thrust of our work in this area was on Lagrangian relaxation methods for the solution of large-scale graphical estimation problems [38, 61, 62], such as those that arise in multi-sensor, multi-target data association. Our new methods provide scalable and potentially distributed algorithms for breaking up otherwise intractable problems into smaller (and tractable), overlapping pieces and then performing iterative optimization, including coordination among the solutions to these pieces in order to guarantee agreement on their overlap. We have provided a version of this algorithm to BAE Systems Advanced Information Technologies.

   More recent components of our work in this area include work on using Belief Propagation for adaptive networking and routing [88] and our work on so-called "feedback message passing." A new approach to distributed fusion in graphical models highlights the role of key nodes. This method makes use of the notion of a *feedback vertex set*, i.e., a set of nodes that, if removed, render a graph cycle-free. With such a set identified, a new messaging algorithm results in which several message streams are created, culminating in fusion at the feedback vertex nodes and subsequent messaging to disseminate information throughout the graph. This algorithm provably gives exact answers for Gaus-

sian inference but is computationally tractable only for graphs with modest-sized feedback vertex sets. More generally, we have developed a method for choosing a set of most important vertices – i.e., ones that are the most significant "information hubs" for the graph and we then employ the same algorithm but now using only a set of these important hub vertices. The resulting algorithm yields approximate answers (since not all loops in the graph have been broken), but our results demonstrate that excellent and scalable performance is readily achieved using only modest-sized sets of hub vertices, including for graphical models for which previously developed algorithms fail to converge. The work that has been documented to date in [68, 69] describes this approach in detail for Gaussian models. Our most recent (but yet to be documented) work deals with using this feedback concept both for scalable sampling from such models and for inference in non-Gaussian (and in particular discrete-valued) processes.

2. Team-Theoretical Algorithms for Distributed Decision-Making (Willsky & Fisher).

   This work focuses on developing team-theoretic algorithms for distributed decision-making in which both data and decision-making responsibility are distributed throughout the network. In this case each node must build models both for the probabilistic meaning of messages that the node receives from other nodes and for the cost resulting from messages that the node sends to others (in terms of the decisions made by those nodes directly and indirectly through subsequent messaging to still other nodes). Formulating these problems as team-optimization problems and invoking the concept of person-by-person optimality, we have developed message-passing algorithms that allow nodes to build these required models – i.e., to develop what we refer to as fusion protocols for interpretation of received messages and for local objectives for generating messages to be transmitted. We first developed this framework in the context of purely feed-forward networks in which, while decision-making and data are distributed throughout the network, communication is allowed only along a directed acyclic graph. In this context we have demonstrated that, depending on the distributed fusion structure, e.g., which nodes are responsible for which decisions, it may be better to use message-passing networks that differ from the underlying graphical structure of the underlying variables being sensed. We also developed a generalization to problems in which communication can be two-way. In this case true optimality is quite complex, as the bits transmitted by each sensor can convey two types of information, namely, information of value to the receiver as well as information to guide that receiver in what it will transmit back to the originating sensor. Hence this formulation captures both information-push and information-pull. We developed suboptimal, principled, and tractable solutions to this problem.

   Another portion of our research involved the exploitation of new methods in nonparametric Bayesian analysis – namely those involving so-called Dirichlet Processes and Hierarchical Dirichlet Processes, which allow an effective method for learning models for complex behavior without pre-specifying the degree of that complexity. For example, [12] provides a new method for target tracking and data association without having to explicitly postulate or enumerate the different numbers of targets present. The work in [13-14] deals with developing models for maneuvering targets in which we learn maneuver modes for the targets without prior knowledge of their nature or the number of different modes. Generalizations of these methods to discovering more complex hidden dynamic behavior in terms of switching modal behavior (modeled via an HMM with an unknown state space) and dynamics (in terms of the details of dynamics of the observed time series) are documented in [55–58].

   We have also had great success in another component of our research, namely an approach blending so-called level-set methods and dimensionality reduction to learn high-performance processing methods for discrimination tasks in both centralized and networked systems [102–104]. The idea behind these methods is to use available training data both to identify lower-dimensional projections

of the data of most significance for the discrimination task as well to determine decision boundaries in these reduced-dimension spaces via curve evolution. A distributed version also allows this to be accomplished with limited communication among sensing nodes.

3. Learning Tractable Models for Complex Sources of Data and for Characterizing the Performance (Willsky & Fisher).

   The last major component of our research deals with several different approaches to learning tractable models for complex sources of data and for characterizing the performance of these algorithms. A first part of this work developed methods for identifying graphical models, where the explicit objective is to build models that are of most value for discrimination tasks [90, 96]. This is of considerable importance in problems in which we have high-dimensional data (e.g., from many sensors) but comparatively few samples compared to the data dimension. In such a case building, say, maximum likelihood models for each class to be discriminated is problematic; moreover, such methods are likely to emphasize aspects of the data that explain most of the variability and energy. In our approach, the focus is on saliency, i.e., on identifying models that highlight those aspects of each class that are most useful for discriminating it from other classes. This can often be accomplished with far less data and hence is of considerable value for many surveillance applications.

   A second thrust in learning models is our work on characterizing the performance and scaling behavior of optimal methods for learning graphical models on trees and, more recently, other graphs i.e., in which the structure of the model relating a large set of variables is to be learned from data [92,95,97]. Our work, using methods of large deviations, identifies the most likely errors as well as the error exponent associated with those errors. The work also identifies models that are easiest and most difficult to learn as well as providing scaling laws on how performance depends on the dimension of the model and the available number of samples.

   The final thrust of our research has been on developing methods to discover “hidden” structure in complex data i.e., hidden variables that help explain the complex interactions of variables that are observed and hence provide notions of context in which observed behavior can be interpreted. This work has had two components. The first [48, 49] involves the learning of hidden tree-structured graphical models, with applications in scene understanding and object recognition, in which that hidden structure represents context in which the observed data and objects are embedded. The second [43–46] involves the development of convex relaxations of formulations that seek to recover parsimonious representations of the available data in which parsimony is captured by sparsity of graphical models as well as dimensionality of the hidden variables. Theoretical guarantees and effective algorithms have been developed.

4. Shooter Localization with a Minimal Number of Single-Channel Wireless Sensor Nodes (Koutsoukos & Ledeczi).

   Acoustic shooter localization systems are being rapidly deployed in the field. However, these are standalone systems either wearable or vehicle-mounted that do not have networking capability even though the advantages of widely distributed sensing for locating shooters have been demonstrated before. The reason for this is that certain disadvantages of wireless network-based prototypes made them impractical for the military. Systems that utilize stationary single-channel sensors require many sensor nodes, while the multi-channel wearable version needs to track the absolute self-orientation of the nodes continuously, a notoriously hard task. We have developed an approach that overcomes the shortcomings of past approaches. Specifically, the technique requires as few as five single-channel wireless sensors to provide accurate shooter localization and projectile trajectory estimation. Caliber estimation and weapon classification are also supported. In addition, a single node alone can provide

reliable miss distance and range estimates based on a single shot as long as some reasonable assumption holds. The main contribution of the work is the novel sensor fusion technique that works well with a limited number of observations. The technique is thoroughly evaluated using an extensive shot library. Our results are reported in [76].

5. External Smart Microphone for Mobile Phones (Koutsoukos & Ledeczi).

   Mobile phones are gaining popularity as sensing platforms. They already come with a set of built-in sensors, such as GPS, accelerometer, microphone and radio, enabling interesting applications. Furthermore, several systems exist where external sensors are interfaced with mobile phones to monitor medical conditions or support environmental sensing, for example. We have developed an external acoustic sensor that interfaces with a mobile phone to support continuous monitoring of sounds in the environment [105]. The on-board electronics samples the microphone, performs signal processing and detection tasks and sends the events of interest to the mobile phone via Bluetooth. The main reasons the built-in microphone is not able to support such an application is the high power usage of continuously sampling and processing the acoustic signal on the phone and the fact that the typical phone is carried in a pocket or bag shielding the microphone from the environment. Our particular motivating application is a mobile phone-based countersniper system.

2 Thrust II: Optimal Target Recognition and Tracking Algorithms in Urban Environments

Investigators: Bela Bollobas, Xenofon Koutsoukos, Akos Ledeczi, Shankar Sastry, and Allen Yang.

The focus of Thrust II has been to develop new algorithms and software for tracking and classifying multiple targets in sensor webs. Particularly for human targets, we are interested in recovering their identities, poses, actions, and finally inference of possible adversarial intents. We are also interested in studying autonomous and adaptive mobility of sensor networks in urban environments. One central theme crystallized via collaboration among team members is distributed perception. A key tenet of distributed perception is to push the recognition tasks out to the edge of a sensor network and only enable post-processed observations data in real-time to centralized stations for further processing.

1. High-Dimensional Pattern Recognition via Sparse Representation (Sastry & Yang).

   One of our best-known studies in this area is a recent work on sparse representation-based classification (SRC) and its application in *robust face recognition* [89,106,107,112,115]. Face recognition has enjoyed sustained interest in the community mainly because many of the common image nuisances in face recognition have plagued other vision systems in general: illumination, occlusion, pose, and misalignment. Recent studies have shown that the concept of sparse representation plays a critical role in modeling recognition functions in human vision [107]. Motivated by the emerging theory of compressive sensing, we were among the first to introduce the SRC framework for classification of high-dimensional data, e.g., face images. Using a mixture subspace model, i.e., one subspace model for each learned subject class, the framework stipulates that a valid query sample can be represented as a linear combination of all training samples. Seeking the sparsest solution in such a linear system should lead to nonzero coefficients corresponding only to the training samples of the same class. More importantly, the new SRC framework can effectively handle a large variety of image nuisances. Two examples of the SRC estimation on corrupted face images are shown in Figure 1.

   This sparsity-based classification technique has been reviewed by several technology articles on the Communications of the ACM, ABC News, Wired.com, etc., as “a quantum leap in face-recognition technology.” The work has also been well received and cited outside the face recognition community

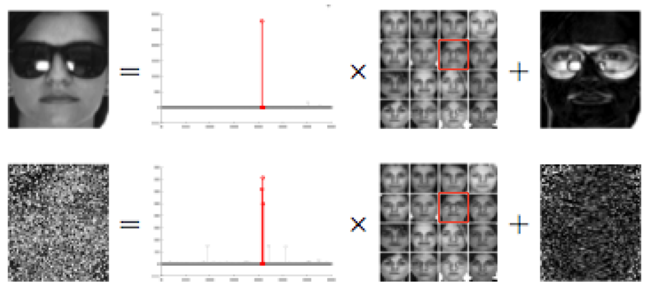

Figure 1: The method represents a query image (left), which is partially occluded or corrupted, as a sparse linear combination of all the normal training images (middle) plus sparse errors (right).

[115], including in image super-resolution, object recognition, human activity recognition, speech recognition, and 3-D motion segmentation. In particular, the paper [107] was a Top 100 Download of IEEE in June, 2010, and has since received more than 800 citations according to Google.

2. Parallelization of Sparsity Minimization Algorithms (Sastry & Yang).

   The transition of many compressive sensing and sparse optimization algorithms to commercially successful solutions often hinges on the availability of efficient numerical solutions. Speed is exactly one of the major barriers to process large-scale databases in the above face recognition application.

   To address this critical issue, we have studied enabling parallel algorithms to support the deployment of the above sparsity minimization problems in distributed sensor networks. We envision a cloud-based architecture can be developed based on modern multi-core CPU/GPU architectures, which will provide a unified computational platform to analyze multi-modal sensor data from ground (e.g., smart phones), air (e.g., aerial vehicles), and outer space (e.g., hyperspectral imaging satellites). Our effort in this direction has led to a prototype real-time face recognition system that can classify high-resolution face images in the wild for up to hundreds of subject classes [106].

   Currently, we are also collaborating with Qualcomm and Texas Instruments to further investigate hardware acceleration techniques on the next generation mobile CPU/GPU platforms (e.g., ARM and OMAP). Extensions of these methods to wireless healthcare applications have also been pursued [60, 108, 110].

3. CITRIC: A Low-Bandwidth Wireless Camera Network Platform (Sastry & Yang).

   we proposed and demonstrated a novel wireless camera network system, called *CITRIC* [47, 116]. The core component of this system is a new hardware platform that integrates a camera, a frequency-scalable (up to 624 MHz) CPU, 16 MB FLASH, and 64 MB RAM onto a single device. The device then connects with a standard sensor network mote to form a *camera mote*, as shown in Figure 2. The design enables in-network processing of images to reduce communication requirements, which has traditionally been high in existing camera networks with centralized processing. We also proposed a back-end client/server architecture to provide a user interface to the system and support further centralized processing for higher-level applications. Our camera mote enables a wider variety of distributed pattern recognition applications than traditional platforms because it provides more computing power and tighter integration of physical components while still consuming relatively little power. Furthermore, the mote easily integrates with existing low-bandwidth sensor networks because it can communicate over the IEEE 802.15.4 protocol with other sensor network platforms.

4. Planning Along Paths and Coverage Holes using Distributed Camera Networks (Bollobas & Sastry).

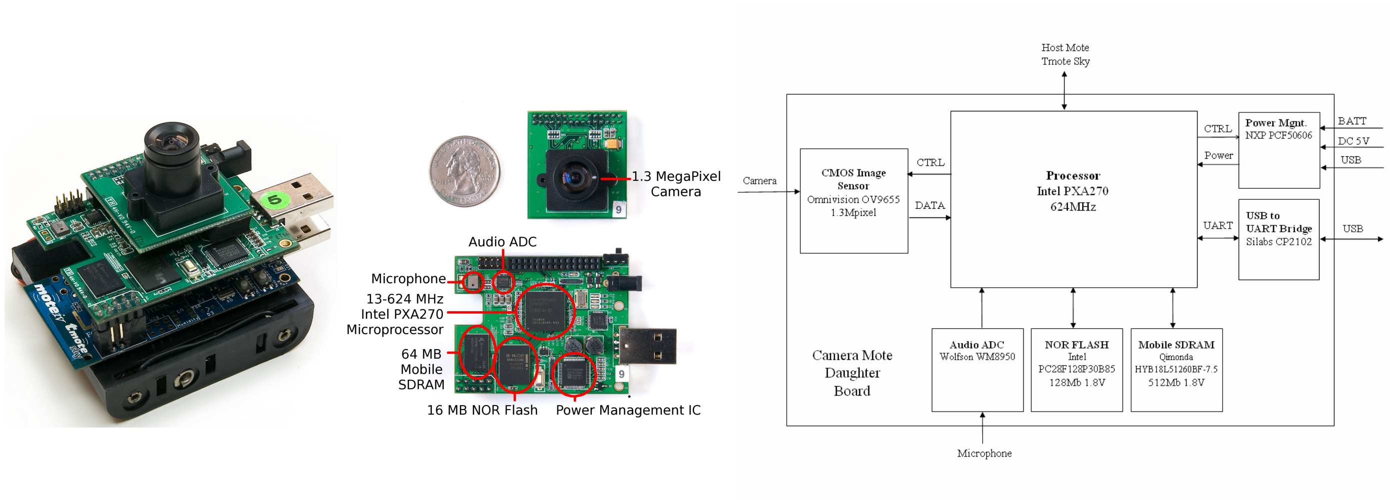

Figure 2: (Left) Assembled camera daughter board with Tmote. (Middle) Camera daughter board with major functional units outlined. (Right) Block diagram of major camera board components.

Distributed camera networks provide rich information about an environment. They have applications in surveillance, emergency response, and pursuit-evasion problems. In this work [70], we proposed a framework for efficiently computing paths for an agent from a start state to a goal state identified in images from the camera views without explicit localization of the cameras. We also show how to identify and plan tight paths around holes in the camera networks coverage resulting from insufficient cameras or geometric features in the environment such as circular corridors.

Prior approaches often require unreliable 3D reconstructions, detailed calibration procedures, or video feed broadcasts to centralized servers that quickly saturate network bandwidth as the size of the network increases. In contrast, we explicitly utilize the distributed nature of the network and assume only that the cameras can robustly track the agent and identify static occluding contours in the images. With this limited information space, we build a distributed simplicial representation that generalizes the notion of a graph and captures accurate topological information about the network coverage. This representation provides the foundation for our planning algorithms, for which we prove their correctness using tools from algebraic topology. Using a simulated environment, we analyze the performance of our approach and demonstrate its effectiveness, scalability, and minimal network bandwidth required.

5. Unsupervised distributed feature selection for multiple-view object recognition (Darrell).

   Object recognition of indexing from multiple views usually offers increased performance when compared to single views. However, in a bandwidth-limited environment, it may be difficult to transmit all the visual features extracted from individual images to perform the task of recognition. We considered the problem of how to select which visual features to send in each camera view to achieve optimal results at a centralized recognition or indexing module, as shown in Figure 3.

   Our study in [50] has shown that it is possible to achieve very efficient encoding without any information exchange between the sensors, by adopting a distributed encoding scheme that takes advantage of known statistics of the environment. We developed a new method for distributed encoding based on a Gaussian process formulation, and demonstrated its applicability to encoding visual-word feature histograms, which are used in many contemporary object indexing and category recognition methods. Our algorithm exploits redundancy between views and learns a statistical model of the dependency

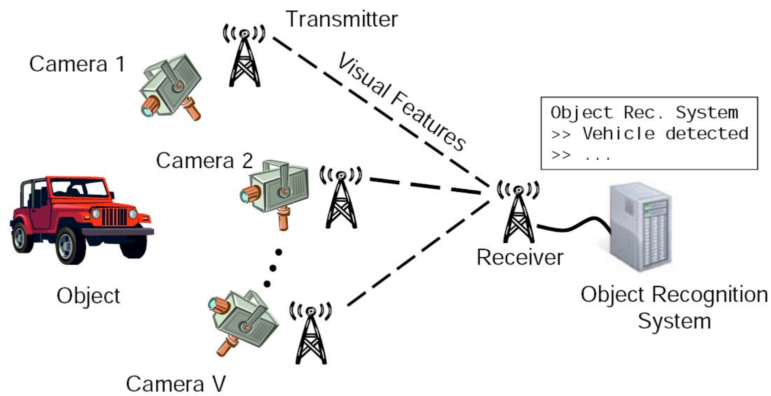

Figure 3: An outline of a distributed object recognition framework. Messages are only sent between the cameras and the recognition module. The system presumes no direct communication between cameras.

between feature streams during an off-line training phase at the receiver. This model is then used along with previously decoded streams to aid feature selection at each sensor. If the streams are redundant, then only a few features need to be sent. As shown in our experiments, our algorithm is able to achieve an efficient joint encoding of the feature streams without explicitly sharing features across views. This results in an efficient unsupervised feature selection algorithm that improves recognition performance in the presence of limited network bandwidth.

6. Transmission Control Policy Design for Decentralized Detection (Koutsoukos & Ledeczi).

   The design of wireless sensor networks for detection applications is a challenging task. On one hand, classical work on decentralized detection does not consider practical wireless sensor networks. On the other hand, practical sensor network design approaches that treat the signal processing and communication aspects of the sensor network separately result in suboptimal detection performance because network resources are not allocated efficiently. In this work, we attempt to cross the gap between theoretical decentralized detection work and practical sensor network implementations. We consider a cross-layer approach, where the quality of information, channel state information, and residual energy information are included in the design process of tree-topology sensor networks. The design objective is to specify which sensors should contribute to a given detection task, and to calculate the relevant communication parameters. We compare two design schemes: (1) direct transmission, where raw data are transmitted to the fusion center without compression, and (2) in-network processing, where data is quantized before transmission. For both schemes, we design the optimal transmission control policy that coordinates the communication between sensor nodes and the fusion center. We show the performance improvement for the proposed design schemes over the classical decoupled and maximum throughput design approaches. Our results are reported in [101].

7. High Precision Radio Interferometric Tracking of Mobile Sensor Nodes (Koutsoukos & Ledeczi).

   During the past 5 years, we have developed an approach for high precision localization, tracking, and navigation of mobile sensor nodes based on radio interferemetry. In the last year, we have finalized the results of TripNav, a localization and navigation system that is implemented entirely on resource-constrained wireless sensor nodes [1]. The main extension is the development of a method for estimating the robot heading based on Kalman filtering. Localization and navigation using this method does not require a digital compass which increases complexity, weight, and cost of the robot. The method is evaluated using extensive error analysis and simulations.

3 Thrust III: Assessment Metrics for Sensor Web Systems

Investigators: Bela Bollobas and Michael Gastpar.

This Thrust is focused on theoretical bounds on the performance of different kinds of sensor networks based on the density of their deployment and the choice of sensing, networking, and signal processing algorithms.

1. Sparse Support Recovery with Noisy Data (Gastpar).

   The fact that sparse vectors can be recovered from a small number of linear measurements has important and exciting implications for engineering and statistics. However despite the vast amount of recent work in the field of compressed sensing a sharp characterization between what can and cannot be recovered in the presence of noise remains an open problem in general. In our work, we have provided such a characterization for the task of sparsity pattern estimation (also known as support recovery). Using tools from information theory we have found a sharp separation into two problem regimes – one in which the problem is fundamentally noise-limited and a more interesting one in which the problem is limited by the behavior of the sparse components themselves. This analysis has allowed us to identify settings where existing computationally efficient algorithms such as the LASSO are optimal as well as other settings where these algorithms are highly suboptimal. Furthermore we have shown how additional structure can make a key difference analogous to the role of diversity in wireless communications.

   On the engineering side our analysis has answered key engineering questions related to compressed sensing: Is it better to increase SNR or take more measurements? Is a given algorithm good enough? What accuracy can be attained? On the mathematical side our results have validated certain phase transitions predicted by the powerful but heuristic replica method from statistical physics.

2. Energy-Latency Tradeoff for In-Network Function Computation in Random Networks (Bollobas).

   The problem of designing policies for in-network function computation with minimum energy consumption subject to a latency constraint is considered. The scaling behavior of the energy consumption under the latency constraint is analyzed for random networks, where the nodes are uniformly placed in growing regions and the number of nodes goes to infinity. The special case of sum function computation and its delivery to a designated root node is considered rst. In this paper we propose a policy which achieves order-optimal average energy consumption in random networks subject to the given latency constraint. The scaling behavior of the optimal energy consumption depends on the path-loss exponent of wireless transmissions and the dimension of the Euclidean region where the nodes are placed. The policy is then extended to computation of a general class of functions which decompose according to maximal cliques of a proximity graph such as the k-nearest neighbor graph or the geometric random graph. The modified policy achieves order-optimal energy consumption albeit for a limited range of latency constraints.

3. Monotone Graph Limits and Quasimonotone Graphs (Bollobas).

   The recent theory of graph limits gives a powerful framework for understanding the properties of suitable (convergent) sequences (G_n) of graphs in terms of a limiting object which may be represented by a symmetric function W on $[0, 1]$, i.e., a *kernel* or *graphon*. In this context it is natural to wish to relate specific properties of the sequence to specific properties of the kernel. Here we show that the kernel is monotone (i.e., increasing in both variables) if and only if the sequence satisfies a "quasi-monotonicity" property defined by a certain functional tending to zero. As a tool we prove an inequality relating the cut and L^1 norms of kernels of the form $W_1 - W_2$ with W_1 and W_2 monotone that may be of interest in its own right; no such inequality holds for general kernels.

4 Thrust IV: 3-D Reconstruction of Large-Scale Environments

Investigators: Shankar Sastry, Allen Yang, and Avideh Zakhor.

In this Thrust, we have proposed two novel 3-D geometric algorithms/systems to reconstruct large-scale urban structures using multiple camera sensors or the integration of mobile camera sensors and depth sensors.

1. A Portable Data Acquisition System for 3-D Modeling of Building Interiors (Zakhor).

   We have developed a human operated backpack data acquisition system equipped with a variety of sensors such as cameras, laser scanners, and orientation measurement sensors to generate 3D models of building interiors, including uneven surfaces and stairwells. The backpack system is shown in Figure 4. An important intermediate step in any 3D modeling system, including ours, is accurate 6 degrees of freedom localization over time. Over the last year, we have developed two approaches to improve localization accuracy over existing methods. First, we develop an adaptive localization algorithm which takes advantage of the environments floor planarity whenever possible. Secondly, we show that by including all the loop closures resulting from two cameras facing away from each other, it is possible to significantly reduce localization error in scenarios where parts of the acquisition path is retraced. We experimentally characterize the performance gains due to both schemes.

   

   Figure 4: The backpack data acquisition system.

   When building 3D textured models, we find that the localization resulting from scan matching is not pixel accurate, resulting in misalignment between successive images used for texturing. To address this, we propose an image based pose estimation algorithm to refine the results from our scan matching based localization. Finally, we use the localization results within an image based renderer to enable virtual walkthroughs of indoor environments using imagery from cameras on the same backpack. Our renderer uses a three-step process to determine which image to display, and a RANSAC framework to determine homographies to mosaic neighboring images with common SIFT features. In addition, our renderer uses plane-fitted models of the 3D point cloud resulting from the laser scans to detect occlusions. We characterize the performance of our image based renderer on an unstructured set of 2709 images obtained during a five minute backpack data acquisition for a T-shaped corridor intersection. In Figure 5, we show the rendering result of a complex multi-floor building interiors using our renderer and the data captured by the above backpack system.

2. Holistic 3-D Reconstruction of Urban Structures from Low-Rank Textures (Sastry & Yang).

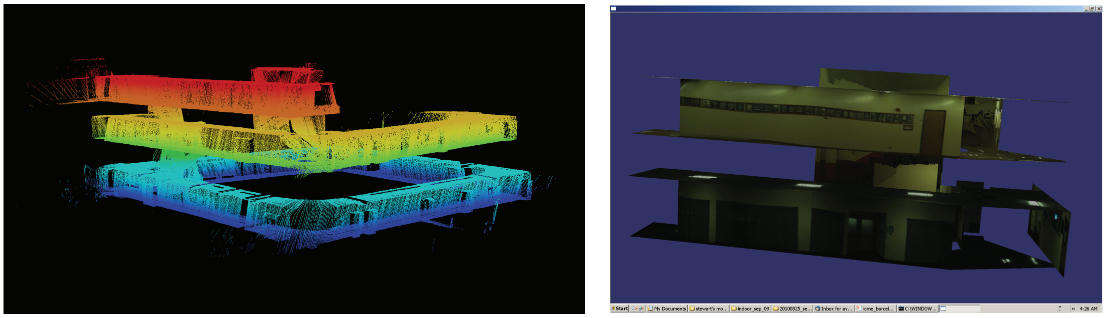

Figure 5: Rendering of an acquired multi-floor building structure: **Left:** Its interior geometry; **Right:** The surface texture images.

Recently, there has been tremendous interest in building large-scale 3D models for urban environments, which are largely driven by industrial applications such as Google Earth, Street View, and Microsoft's Bing Maps, etc. The conventional SFM approach to build a 3D model of a scene typically relies on detecting, matching, and triangulating a set of feature points (and edges) in multiple camera views. In practice, researchers have observed that urban scenes often have very special types of shapes and textures, which may not be ideal for generic SFM techniques. We have recently introduced a new approach to reconstructing accurate camera geometry and 3D models for urban structures in a holistic fashion, i.e., without relying on extraction or matching of traditional local features such as points and edges [72]. Our method relies on a new set of semi-global or global features called transform invariant low-rank texture (TILT), which are ubiquitous in urban scenes. Modern high-dimensional optimization techniques enable us to accurately and robustly recover precise and consistent camera calibration and scene geometry from a single or multiple images of the scene. We have demonstrated the capabilities of our method by showing examples of how to construct 3D models of buildings from multiple uncalibrated images. Some of the examples are shown in Figure 6.

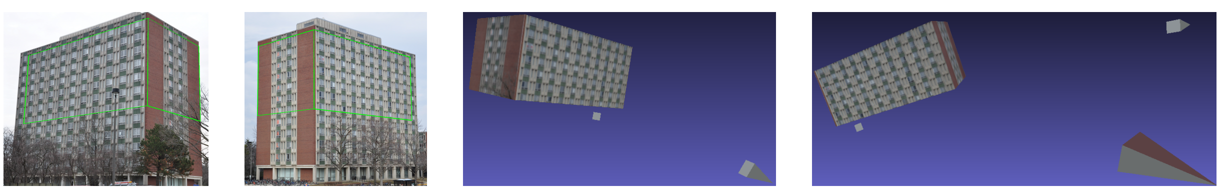

Figure 6: Left Pair: Example of matched facades of the rectangular building. Right Pair: Frontal reconstructed views, where pyramids show the estimated location of cameras.

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